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Insomnia analysis based on internet of things using electrocardiography and electromyography

Novi Azman[1], Mohd Khanapi Bin Abd Ghani[2], S. R. Wicaksono[3], Barru Kurniawan[4], Viktor Vekky Ronald Repi[5]
[1,2]Fakulti Teknologi Maklumat dan Komunikasi (FTMK), Universiti Teknikal Malaysia Melaka, Malaysia
[1,4]Electrical Engineering Department, Universitas Nasional, Jakarta, Indonesia
[3,5]Engineering Physics Department, Universitas Nasional, Jakarta, Indonesia

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ABSTRACT

Insomnia is a disorder to start, maintain, and wake up from sleep, has many sufferers in the world. For patients in remote locations who suffer from insomnia, which requires testing, the gold standard performed requires patients to take the time and travel to the health care center. By making alternatives to remote sleep insomnia testing using electrocardiography and electromyography connected to the internet of things can solve the problem of patients' access to treatment. Delivery of patient data to the server is done to make observations from the visualization of patient data in real-time. Furthermore, using artificial neural networks was used to classify EMG, ECG, and combine patient data to determine patients who have Insomnia get resulted in patient classification errors around 0.2% to 2.7%.

Corresponding Author:

Novi Azman,
Electrical Engineering Department,
Universitas Nasional,
Sawo Manila St., Jakarta Selatan 12520, DKI Jakarta, Indonesia.
Email: novi.azman@civitas.unas.ac.id

1. INTRODUCTION

Sleep is a mandatory requirement that humans need and affect human health. Poor sleep quality can result in sleep disorders that have a direct and indirect impact on daily activities. There is a tendency that patients who have sleep disorders are more prone to suffer from chronic diseases such as diabetes, obesity, and hypertension. Several studies have found an association between sleep quality and the risk of chronic obesity and diabetes [1], while obstructive sleep apnea is a risk factor for systemic hypertension [2].

The most common sleep disease is Insomnia. Insomnia is a sleep disorder that is often overlooked and missed by primary care physicians until or unless requested by the patient, with a prevalence of about one in three subjects in the study that has a sleep disorder insomnia. Prevalence of people with chronic insomnia has increased significantly in the urban area. The urban lifestyle, requirements, and other socio-economy demands are some of the cause for this increment [3-8]. These have an indirect effect on the socio-economy factors in a country, where about 60 percent of people in developing countries living in an urban area.

Polysomnography is the gold standard to measurement and collection of those factor for the sleep study. However, due to the routine of clinical assessment, the polysomnography is impractical and limited to be used in a specific place [9]. A proposed actigraph could be used to increase accuracy and mobility from polysomnography for sleep pattern measurement. Unfortunately, the limitation of this device and complexity in its installation, along with polysomnography become their restriction [10]. The advantage of using this polysomnography is that it produces accurate data, but it has constraints in terms of time and cost needed by patients to be able to get insomnia treatment as well as obstacles for patients who find it challenging to carry out routine treatment to the hospital. However, this conventional approach has been considered more costly and technically complex and may present appointing schedule difficulties when there is high demand [11]. One of the most problems of sleep disorder is access to diagnosis. The demand of the diagnosis is influenced by prevalence and incidence of the disease, cost and patient reimbursement policies, patient and primary physician awareness and wait times where the capacity of the treatment dictate by availability of sleep laboratory beds determined by funding policies, availability of sleep specialists, and policies about order or interpret diagnostic polysomnography studies [12]. Treatments and assessments of insomnia using polysomnographic turn out to have socio-economic problems, but for some cases is not good enough in patients who are difficult to mobility [13, 14]. So we need a tool with a method of use that can make it easier for patients to undergo treatment that is cheap and easy to apply daily.

The use of internet-based telemonitoring with the advantage of remote data measurement as one of the right solutions to solve the problems faced by insomnia patients. The problem of insomnia patients in terms of time, cost, and routine care that requires patients to come to the hospital. Many IoT application was using in medical area, such as, ECG IoT based centralized insomnia system [15, 16], IoT for diabetes management [17], drowsiness detection and monitoring using IoT and brainwaves [18], IoT for chronic metabolic disorder [19], IoT-based upper limb rehabilitation assessment [20], HRV monitoring using IoT [21], and even for elderly monitoring using IoT [22].

Kuna et. al. [23], was studied about web-based access to positive airway pressure patient, which that disorder is one of sleep apnea. In study, there is significantly improved by giving patient, web access information is used when patient is in treatment. Web access of patient treatment despite the gradual decline in positive airways pressure than usual 3 months of observation. Web-based approach provide patient with information of their treatment was improve healthcare delivery and patient self-management.

Problems that occur regarding access to insomnia sleep disorders testing with high costs and time consuming are expected to be resolved with the help of the internet of things, wherein this study case studies were carried out in remote monitoring of vital organs of the heart using ECG sensors and vital organs of the muscles by using EMG sensors. The results of the data are transmitted using the concept of the internet of things to store data. Furthermore, vital patient data visualized graphically and analyzed for the classification of insomnia sleep disorders. It is also increasing the effectiveness of sending data between patients and medical services. Web-based of information patient treatment which significantly improve insomnia patient treatment.

The contribution of our study is to provide a new system approach to diagnose insomnia sleep disorders. By using some biomedical sensors from polysomnography devices, electrocardiography, electromyography and by applying the concept of the internet of things that is used so that diagnosis can be done anywhere by sending data to the medical center. In this study, it is expected to reduce the cost and time of patients compared to the way the diagnosis of the conventional insomnia sleep disorder nowadays.

2. RESEARCH METHOD

This section will explain how the system created can be useful to perform functions such as the objectives stated in the introduction. Overall, the system in this study is divided into four major parts. This system consists of a hardware system, a software system, communication between them, and the data classification step. In this paper, we will explain how each hardware component is connected. Also explained the process of how the communication between hardware and software data exchange. So finally, how to classification patients with insomnia sleep disorders.

2.1. Hardware systems architecture

The hardware part involved in the system in the study conducted in this paper involves several hardware devices. The hardware made compact so that it makes it easy for the hardware to move from one location to another. Therefore, the hardware made with some lightweight components and small size. Overall, the hardware components that are compiling into a hardware system used in this study are shown in Figure 1.

In Figure 1, we can see that we can group them into four parts. The part is microcontroller and shield, medical sensor, interface, and supply. In the microcontroller and shield section, the ESP32 microcontroller hardware used as the central control of the hardware. The ability of ESP32 [24] using Xtensa® LX6 microprocessors and 448 KB ROM and 520 SRAM also with built-in WiFi 802.11 b/g/n connectivity and bluetooth v4.2 and bluetooth low energy is sufficient to process from the internet of things to the system carried out on the study. Shields made for ESP32 microcontrollers are custom made that is used to connect them to sensors. This section serves to receive data from sensors and send data to the server using internet connectivity.

In the medical sensor section, there are two medical sensors, namely electrocardiography and electromyography sensors. For sensors that record heart activity, the AD8232 electrocardiography medical sensor used. Meanwhile, to record the activity of the body's movements used electromyography medical sensors from BITalino. BITalino is one of the medical sensors used to carry out physiological computing [25, 26]. The placement of electrocardiography medical sensor is using three-lead, which is in Einthoven’s triangle placement and electromyography medical sensor is located at thorax, abdomen, and each of leg. The interface part displays the status of the hardware system in the system used in this study. LCD5110 used as a hardware component whose job is to display the status of the hardware system. The Supply Section is responsible for providing power for the entire hardware system, and a Li-Po battery is used to deliver and distribute power.

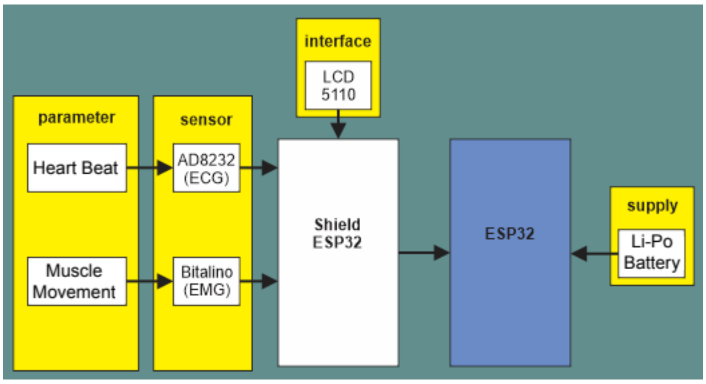

Figure 1. Hardware systems architecture

2.2. Software embedded

Software embedded in the hardware system is carried out using the Arduino IDE program. The process flow is shown in Figure 2. It can seem that at the beginning of the initials, the program is calling the library from the sensor, declaring WiFi profiles, server addresses, and other global variables. Arduino IDE setting the baud rate speed of 115200 bits per second to download the program on the ESP32 microcontroller and logging the processes that occur. Next is to connect to a WiFi network. If the ESP32 microcontroller is not connecting to a WiFi network, it will be re-connecting. If it is successfully connecting to a WiFi network, continuous data reading is performing on the “**void loop()**” function on the arduino programming. Patient vital data readings are from electrocardiography and electromyography sensors with float data types. After the data obtained, then try to connect to the server. If it is not connected, it will reread the patient's vital data and re-connect with the server. If it is connected, the patient's vital data will convert into a form of data string which is carried out for sending data to the server using the "POST" method from REST (representational state transfer) API (application program interface) prepared on the server-side. The process of the **loop()** function will repeat until it doesn’t get power back.

2.3. Communication

This section is communication between systems located in remote areas and servers using interconnection networks. The system is conducting communication between systems located in remote areas sending data to a server where the server acts as a REST API. The connection flow process of the device system at a remote location with a server is shown in Figure 3. The process in Figure 3 starts from the initiation of the user and the website host to log in to the database. Data received through the REQUEST method in REST API will then stored in each table in the MySQL database that is set depending on the type of sensor type used by using the INSERT command in the database. Furthermore, using the API for each table by taking data from the database which convert into the JSON format.

The schematic process flow for creating the API is shown in Figure 4. The schematic is to explain how the patient data flow is taken from the database preparing the data used to be the JSON format. First, initiating website users and hosts who then log in to the database on the web service. Retrieve data from each sensor table from the database using the GET command on MySQL. After the patient data took, then the next step sorts the data according to needs and makes an array of patient data lines. Next is to convert the data array created previously into data in the form of the JSON format.

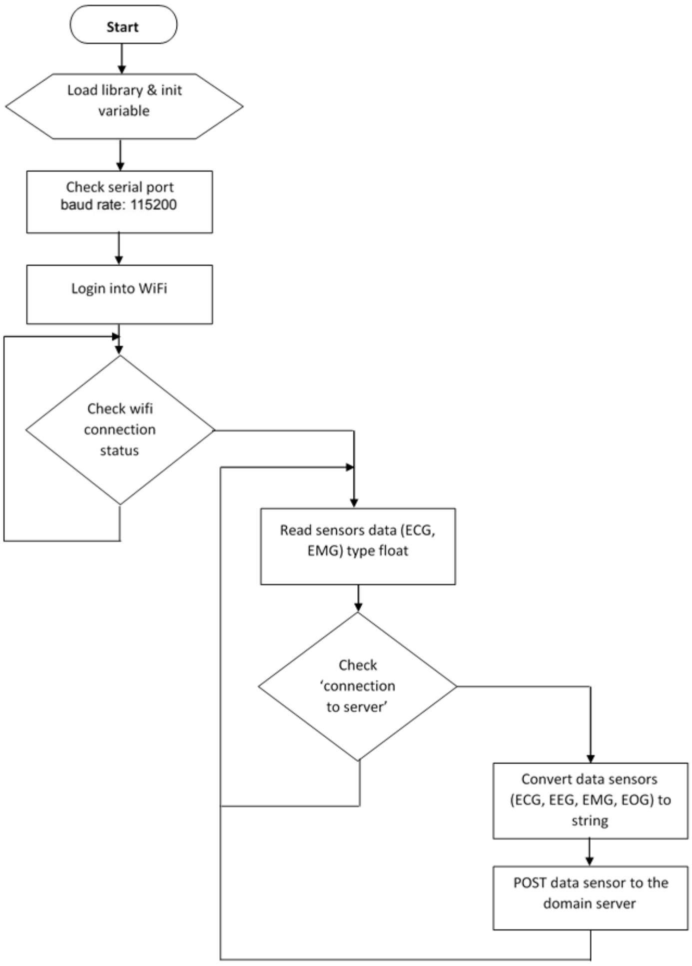

Figure 2. Hardware processing flowchart

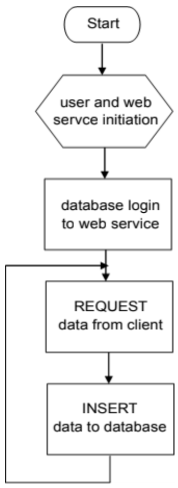

Figure 3. File request data process flowchart

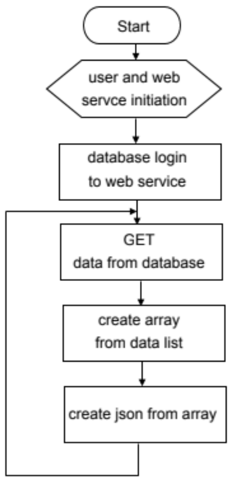

Figure 4. API process flowchart

2.4. Insomnia classification

In classifying patients suffering from insomnia sleep disorders, the process of testing the data with the first artificial neural network aims to compare the patient's cardiac activity test data obtained from electrocardiography sensors with training data from medical devices. The second process is to test data with artificial neural networks that compare the patient's movement data during sleep conditions from electromyography sensors with data from medical devices. The predicted output is the result of comparison with actual output. If the predicted output approaches the value of one of the actual outputs with the smallest error value, then it can be concluded that the predicted output is classifying according to specified conditions. These two processes are shown in Figure 5, the process of comparing data using artificial neural networks as shown in Figure 5 (a).

Furthermore, the last process is to classify insomnia. Insomnia classification derives from two combined data between the predicted output from ECG and EMG data compared with actual output from medical data. If the results obtained from patients approach one of the values of the actual output with the smallest error value, then the conclusions of the measured patient data can be included in the classification according to the specified conditions. The process in classification shown in Figure 5 (b).

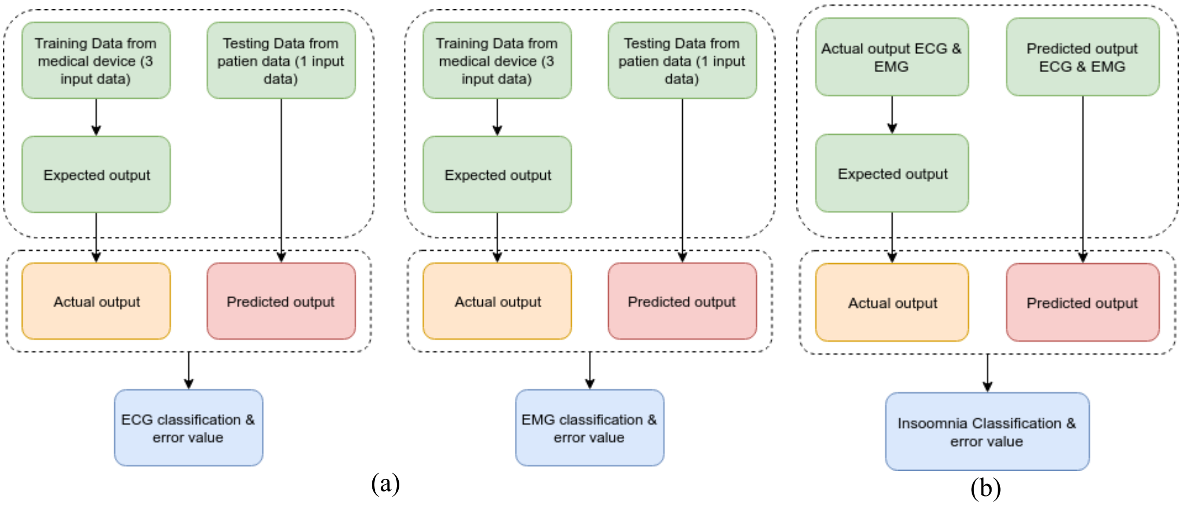

Figure 5. (a) Comparison process of training and testing data using artificial neural network, (b) Insomnia classification' process using artificial neural network

3. RESULTS AND ANALYSIS

3.1. Effectiveness of sending data

The effectiveness of sending data needs to be examined further because in some cases in remote locations, signal strength may be worse than in urban locations; therefore testing with varying signal strengths appears in this study. We can see in Table 1, a comparison of data with varying signal strengths. Table 1 is the data sent from the ESP32 microcontroller which has been set up by sending two data per second (7200 data per hour) with the condition that the tested signal strengths range from -81 dBm to -108 dBm. Delivery time starts from 30 minutes to 120 minutes. It is seen that the accuracy of the signal transmission reaches 100% at the signal strength of -81 dBm, -89 dBm and -97 dBm. While the signal strength of -108 dBm has an accuracy of sending data above 97%. From this data shows that the quality of internet connectivity used must be stable.

Table 1. Sending data accuracy

No	Sending time (in hours)	Amount of packet data	Signal Strength -108 dB m Data received	Accuracy	-97 dB m Data received	Accuracy	-89 dB m Data received	Accuracy	-81dB m Data received	Accuracy
1	0.5	3600	3560	98.80%	3560	100.00%	3560	100.00%	3560	100.00%
2	1	7200	7020	97.50%	7020	100.00%	7020	100.00%	7020	100.00%
3	1.5	10800	10580	97.90%	10580	100.00%	10580	100.00%	10580	100.00%
4	2	14400	14080	97.70%	14080	100.00%	14080	100.00%	14080	100.00%

The effectiveness of sending data is useful for performing patient vital data from electrocardiography and electromyography sensors in real-time. The patient real-time data store in a database. The visualization is a dynamic graph, where this graph will only display the latest data when the device system that is in a remote location is running. So that when it is not running, no graph is displayed. Because the dynamic graph that is displayed is a real-time graph, the use of stable internet connectivity is a must.

3.2. Insomnia classification

Data stored on the server in addition to visualization by making dynamic charts also the data is useful for classifying insomnia, whether the patient has insomnia or not. By using artificial intelligence through artificial neural network methods performed on the server. Patient data will be test data and compared with training data derived from verified medical device data. There are three stages of the process of using artificial neural networks to obtain patient classification results.

In the artificial neural network that uses, there is an input layer and target output, where there are ten arrays of data from three patients which are training data that become the input layer and one expected output target. With the initiation of the number of layers used in the form of ten input layers, ten hidden layers, and one output layer. Test data from the sensor as much as ten arrays of data from the training data compare with ten arrays of test data, which is the input layer. One in ten hidden layers consists of neurons that receive each data from ten input layers. The results in the output layer are a calculation of the value of the input layer to be the target output.

Training data used to train training data, where the training data used is data from medical devices. There are three training data inputs from medical devices provided that two data are not insomnia data, and one is insomnia sufferer data. Each input value will classify with the output value agreed with the specialist doctor. Later the training data will go through a training process until corrections to the agreed, and expected output values are reaches. The value of training used is 350, where the value of this training has the smallest error of the whole tested. These results are shown in Table 2. ECG analysis is shown in Figure 6, is a conclusion from the results of the analysis of patient biosignal data using the BioSppy library, graphs are filtered, analyzed for cardiac activity and reviewed with the PQRST signal pattern displayed in the "Templates" image column.

Table 2. Data training and error of output

No	Train	Error Output	No	Train	Error Output
1	10	25.8 %	9	300	3.1 %
2	30	22.6 %	10	350	1.0 %
3	50	22.3 %	11	400	8.4 %
4	80	15.2 %	12	450	9.1 %
5	100	11.9 %	13	500	9.9 %
6	150	11.9 %	14	550	8.0 %
7	200	6.2 %	15	600	8.8 %
8	250	3.2 %			

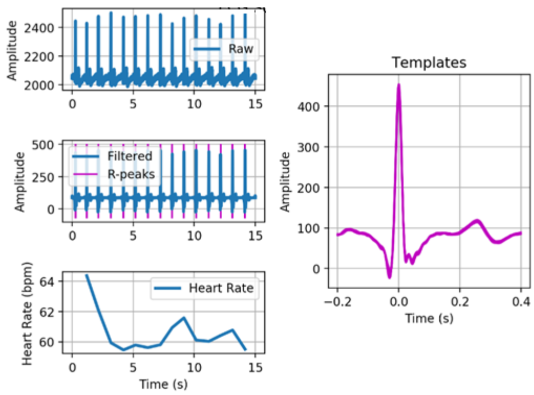

Figure 6. ECG graph analysis in web services

Table 3 is the result of testing ten test data from the device used in this study, namely the electrocardiography sensor, which compares with medical training data. Actual output is the result of the training from the expected output. The predicted output of the device used in this study is compared with the actual output to find the closest data with the smallest error in one of the target values. There are four out of ten test data that are classified as having cardiac abnormalities but have not been confirmed to suffer from insomnia. The error value of this test is between 0.4% and 1.2%. Error mean difference between actual output and predicted output.

Figure 7 shows the conclusions of the EMG conducted by the BioSppy library. In Figure 7, the upper part is the image before filtering by the BioSppy library while at the bottom is the image that has been filtered by the BioSppy library. Table 4 is the result of testing ten test data from the device used in this study, namely the electromyography sensor, which compares with medical training data. Actual output is the result of the training from the expected output. The predicted output of the device used in this study is compared with the actual output to find the closest data with the smallest error in one of the target values. There two of ten test data are classified experiencing tense muscles but has not been confirmed to suffer from Insomnia. The error value of this test is between 0.1% to 1.8%. Error mean difference between actual output and predicted output.

Table 3. ECG analysis using artificial neural network

No	Obtained Data	Medical Device Data			Training Result			Error	Classification Result
		Healty Heart	Healty Heart	Heart Trouble	Train	Actual Output	Predicted Output		
1	[1.1,1.2,2.4,0.9,1.3,1.4,1.3,1.3,1.3,1.3]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.961	0.6%	Healty Heart
2	[1.4,1.2,2.4,1.0,1.3,1.4,1.3,1.3,1.5,1.5]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.935	0.6%	Healty Heart
3	[1.8,1.6,2.9,1.2,1.6,1.8,1.8,1.7,1.6,1.5]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.991	1.0%	Heart Problem
4	[1.6,1.8,2.8,1.2,1.5,1.6,1.8,1.7,1.5,1.8]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.97	1.2%	Heart Problem
5	[1.7,1.7,2.8,1.2,1.5,1.6,1.8,1.7,1.7,1.7]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.99	0.90%	Heart Problem
6	[1.2,1.2,1.6,1.6,2.0,2.3,2.0,1.4,1.7,1.2]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.967	1.2%	Healty Heart
7	[1.4,1.4,2.2,2.4,2.4,1.9,1.4,1.4,1.4,1.3]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.947	0.8%	Healty Heart
8	[1.1,1.2,2.4,1.0,1.3,1.4,1.3,1.3,1.2,1.4]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.951	0.5%	Healty Heart
9	[1.4,1.4,2.3,0.9,1.3,1.4,1.3,1.3,1.4,1.2]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.959	0.4%	Healty Heart
10	[1.6,1.8,2.8,1.1,1.6,1.7,1.8,1.7,1.6,1.6]	[1.5,1.2,2.4,0.8,1.5,1.6,1.7,1.5,1.5,1.2]	[1.3,1.4,2.4,1.0,1.3,1.4,1.3,1.3,1.4,1.4]	[1.8,1.7,2.9,1.2,1.6,1.7,1.8,1.7,1.5,1.8]	350	0.940, 0.955, 0.981	0.993	1.2%	Heart Problem

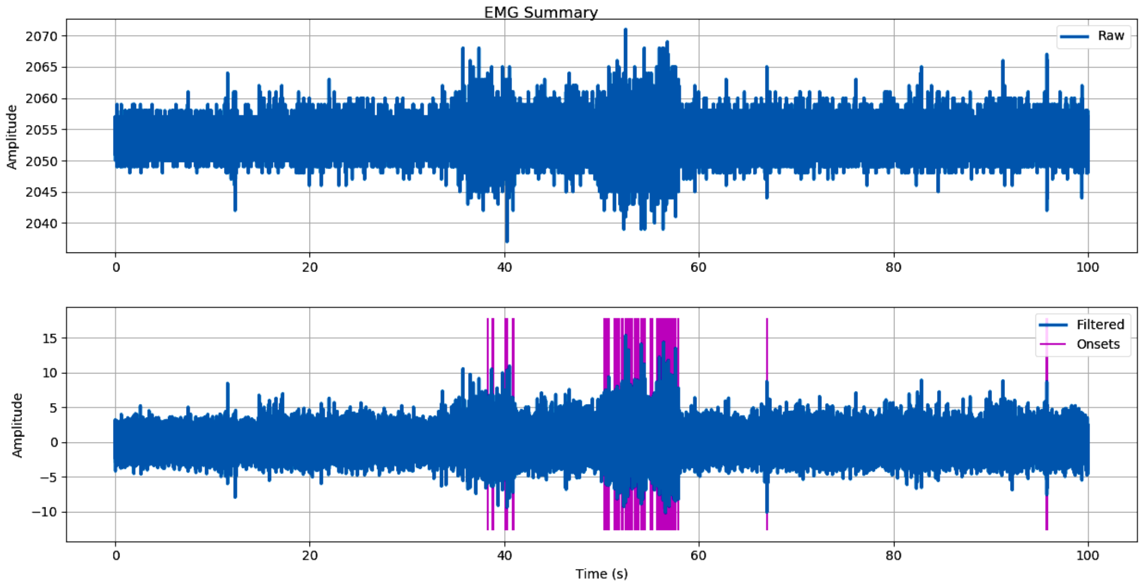

Figure 7. EMG graph analysis in web service

Table 4. EMG analysis using artificial neural network

No	Obtained Data	Medical Device Data			Train	Training Result		Error	Classification Result
		Relax	Relax	Tense		Actual Output	Predicted Output		
1	[1.1,1.3,1.9,2.4,2.4,2.3,1.9,1.3,1.3,1.7]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.91	0.1%	Relax Muscle
2	[1.8,1.8,2.0,2.6,2.3,2.2,1.8,1.7,1.8,1.7]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.929	1.0%	Relax Muscle
3	[1.4,1.4,2.2,2.3,2.4,1.7,1.3,1.3,1.3,1.3]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.92	1.0%	Relax Muscle
4	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.98	0.6%	Tense Muscle
5	[1.9,1.7,2.0,2.7,2.8,2.5,1.9,1.7,1.8,1.7]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.993	0.7%	Tense Muscle
6	[1.4,1.4,1.6,1.8,2.0,2.4,2.0,1.4,1.7,1.2]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.908	1.2%	Relax Muscle
7	[1.3,1.4,2.2,2.4,2.4,1.9,1.4,1.5,1.3,1.4]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.922	0.3%	Relax Muscle
8	[1.7,1.8,2.0,2.2,2.4,2.3,1.8,1.8,1.7,1.7]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.934	0.5%	Relax Muscle
9	[1.0,1.1,1.8,2.2,2.3,2.0,1.7,1.3,1.3,1.3]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.902	1.8%	Relax Muscle
10	[1.6,1.8,1.6,1.8,2.0,2.4,2.0,1.8,1.7,1.7]	[1.8,1.7,2.1,2.4,2.4,2.0,1.8,1.7,1.8,1.7]	[1.3,1.4,2.2,2.4,2.4,1.9,1.3,1.3,1.3,1.3]	[1.8,1.7,1.8,2.7,2.8,2.5,1.8,1.7,1.8,1.7]	350	0.938, 0.919, 0.983	0.928	1.1%	Relax Muscle

Table 5 is the result of testing ten test data from the device used in this study, namely the Electrocardiography sensor, which compares with medical training data. Actual output is the result of the training from the expected output. The predicted output of the device used in this study is compared with the actual output to find the closest data with the smallest error in one of the target values. The range of actual output values of 50 to 65 is insomnia sufferers while in the range of 35 to 45 is insomnia sufferers. The results obtained that there are four out of ten test data classified as suffering from insomnia sleep disorders. Errors of this classification that occur between 0.2% to 2.7%. Error mean difference between actual output and predicted output. Other study using deep learning to classification of insomnia using sleep stages was get accuracy 92% and 86% [27], which is our approach seems promising to classification insomnia patients. One of the results of insomnia classification using artificial neural networks, shown in Figure 8.

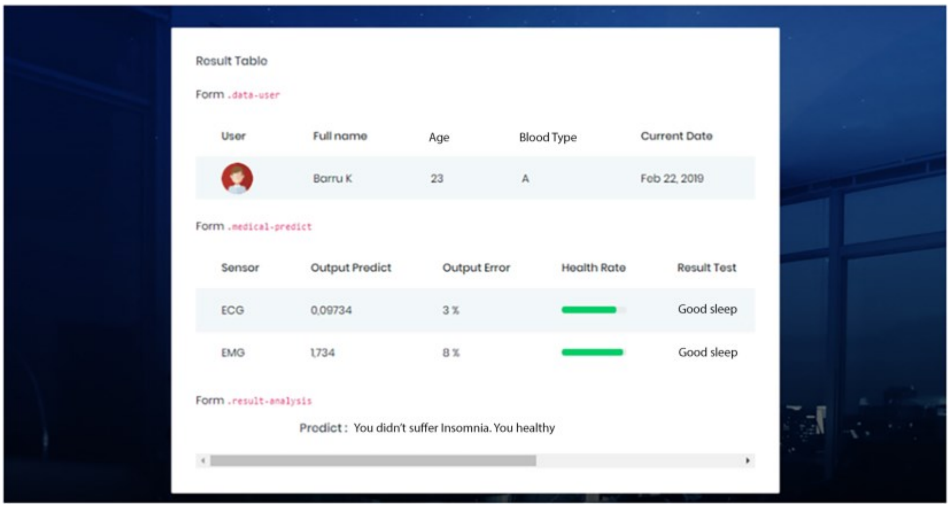

Figure 8. Classification result in web service

Table 5. Insomnia classification using artificial neural network

No	Train	Training Result Actual Output	Predicted Output	Error	Classification Result
1	350	[65], [60], [55], [50], [45], [40], [35]	63.2	2.7%	Non insomnia
2	350	[65], [60], [55], [50], [45], [40], [35]	60.9	1.5%	Non insomnia
3	350	[65], [60], [55], [50], [45], [40], [35]	44.1	2.0%	Person with insomnia
4	350	[65], [60], [55], [50], [45], [40], [35]	39.8	0.5%	Person with insomnia
5	350	[65], [60], [55], [50], [45], [40], [35]	40.4	1.0%	Person with insomnia
6	350	[65], [60], [55], [50], [45], [40], [35]	54.2	1.5%	Non insomnia
7	350	[65], [60], [55], [50], [45], [40], [35]	59.1	1.5%	Person with insomnia
8	350	[65], [60], [55], [50], [45], [40], [35]	58.9	1.9%	Non insomnia
9	350	[65], [60], [55], [50], [45], [40], [35]	60.7	1.1%	Non insomnia
10	350	[65], [60], [55], [50], [45], [40], [35]	40.1	0.2%	Person with insomnia

4. CONCLUSION

Based on the results obtained in this study, we can conclude the following. Signal strength is very influential in sending data sent from the microcontroller to the server. Where in this study, the results obtained with the signal strength of -81 dBm to -97dBm to get 100% accuracy of data transmission. While testing at -108 dBm gets an accuracy above 97%. From the analysis of patient data obtained, it takes about 350 training data, which produces the smallest error. Prediction results from 10 EMG sensor test data, there are 2 out of 10 data that suffer from tense muscles. The resulting accuracy level is 100%, with the most significant error value of 1.8%, and the smallest error is 0.1%. Prediction results from 10 ECG sensor test data, there are 4 out of 10 data that suffer from heart problems. The resulting accuracy level is 100%, with the most significant error value of 1.2%, and the smallest error is 0.4%. The accuracy of classification of people with insomnia with neural network reaches 100%. There are 4 out of 10 data that are predicted to suffer from insomnia. The smallest error value is 0.2%, and the most significant error value is 2.7%. With these results, the diagnosis of insomnia using our system in this study can provide a solution to make a remote insomnia diagnosis that is more cost effective and less time-consuming. For further studies, it is recommended to use other biomedical sensors that are more complete and more equal than the gold standard for testing insomnia such as adding medical sensors EEG, EOG, and other medical sensors that can equal specification with polysomnography device. These results appear in a web-based form with the hope that these results can reach patients in remote locations and doctors in large cities can see data from patients in order to be able to right treatment.

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